MIPT Data Visualization Course

Data Visualization in Modern Machine Learning

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November 16, 2016

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- Low Rank Way (SVD, Auto-encoders, LDA, etc.)
- Generative Models Way (GAN, Image Capturing, etc.)

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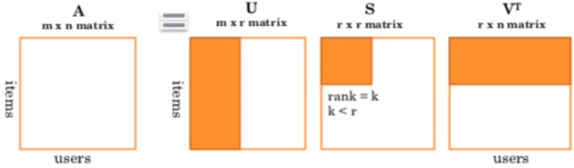

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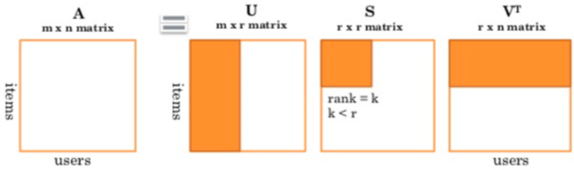

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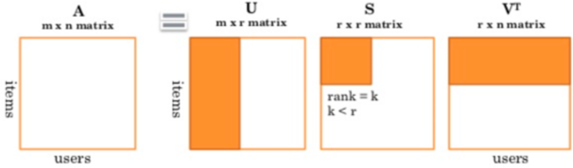

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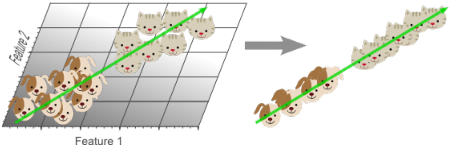

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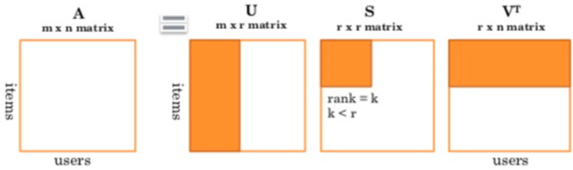

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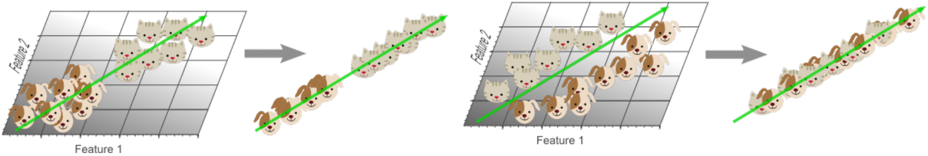

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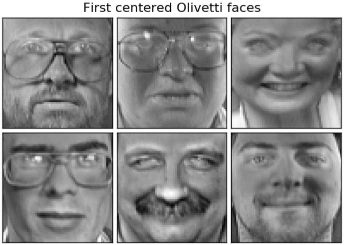

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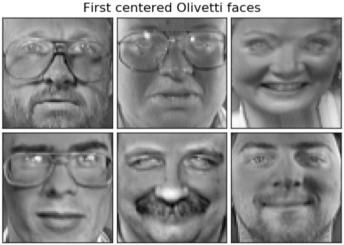

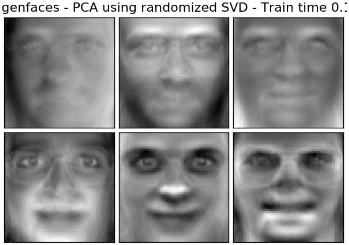

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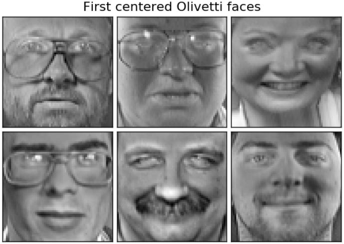

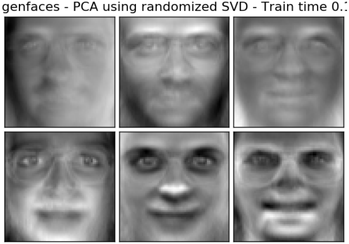

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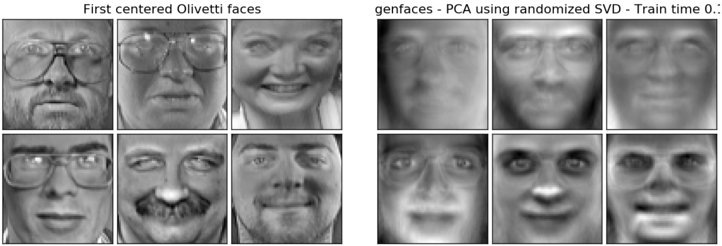

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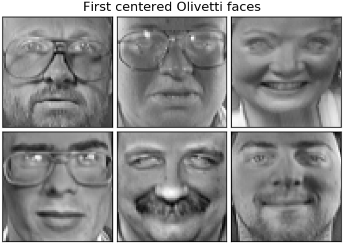

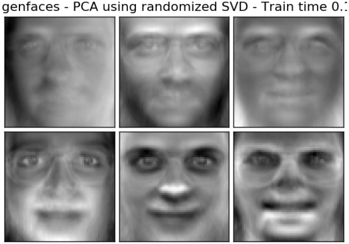

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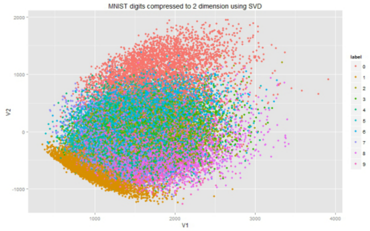

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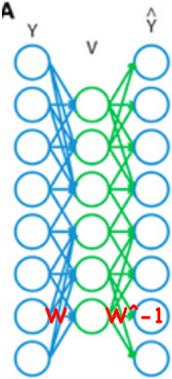

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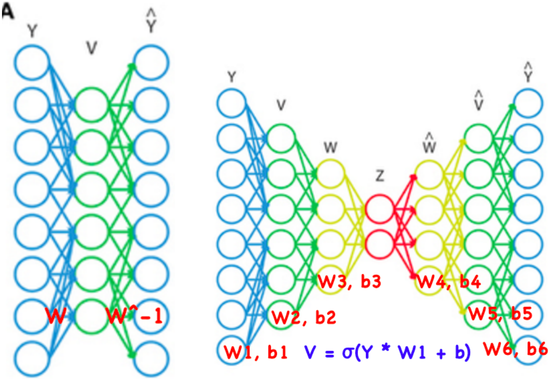

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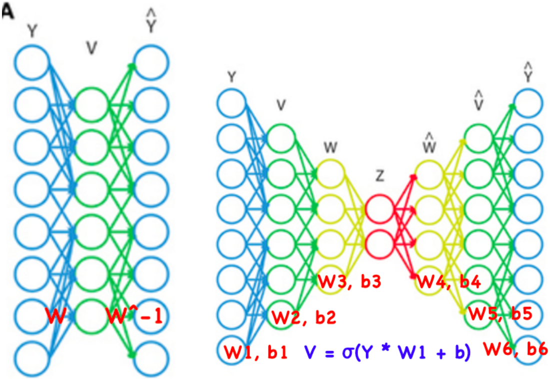

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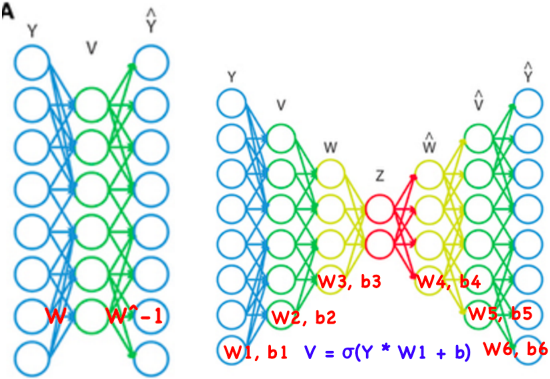

- How to find W_n, b_n?
- Define loss function $L(Y, \hat{Y})$ and use your favourite opt method.

Auto encoders example

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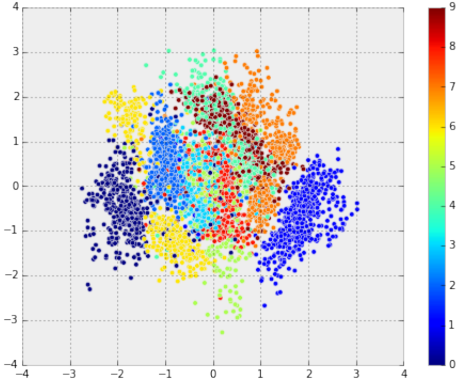

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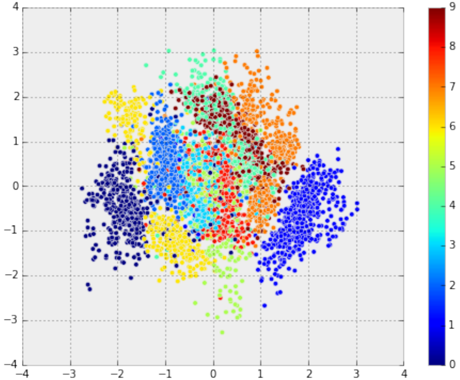

http://dpkingma.com/sgvb_mnist_demo/demo.html

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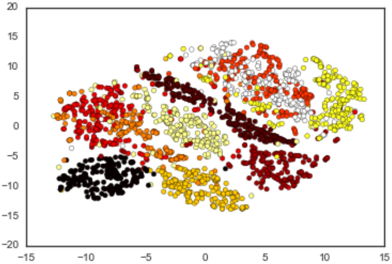

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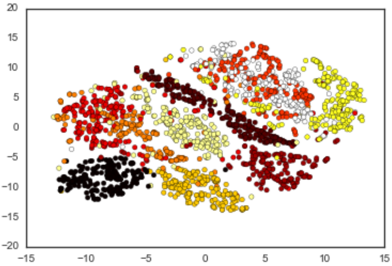

Deep Neural Nets + t-SNE (modification of SNE with Student test):
http://cs.stanford.edu/people/karpathy/cnnembed/

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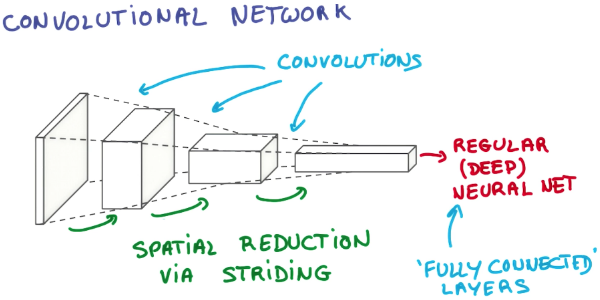
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SPATIAL REDUCTION VIA STRIDING
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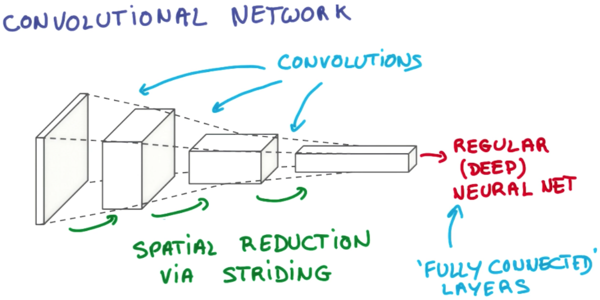
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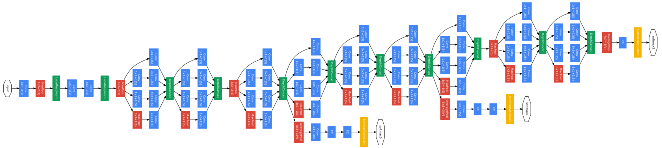

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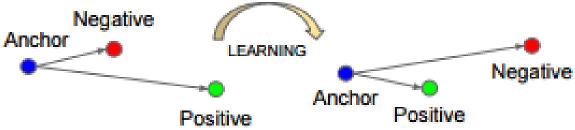

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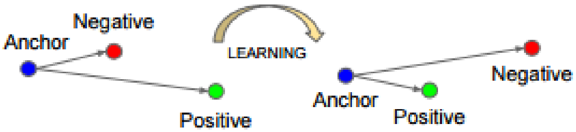

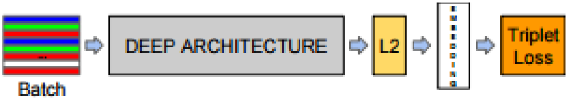

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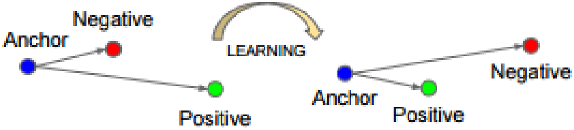

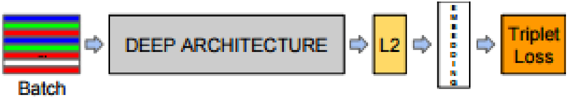

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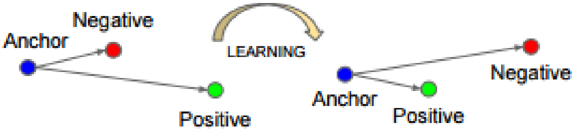

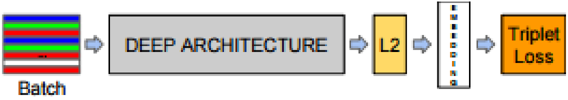

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$$\sum_{i}^{N} \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha \right]_+$$

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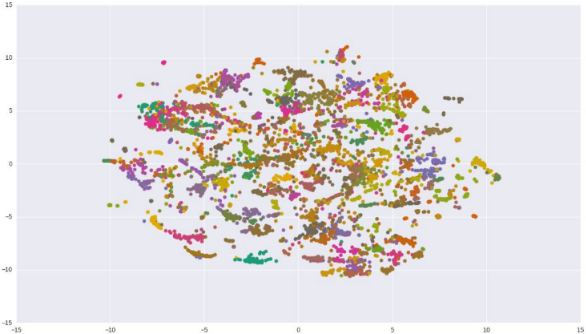

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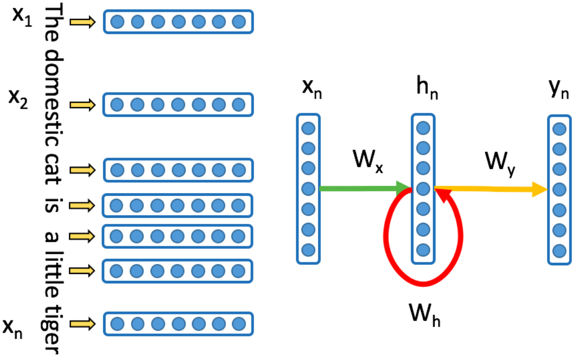

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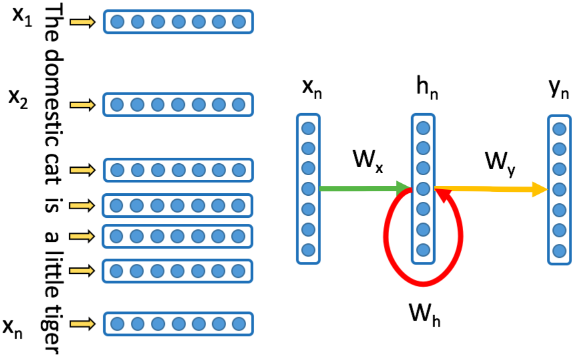

$$h_n = W_x x_n + W_h \sigma(h_{n-1})$$

$$y_n = \sigma(W_y h_n)$$

Word2Vec

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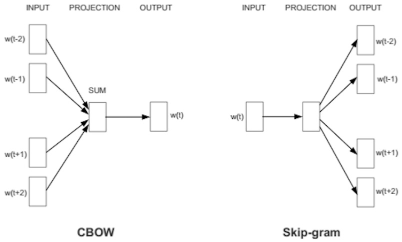
- Shallow Neural Net



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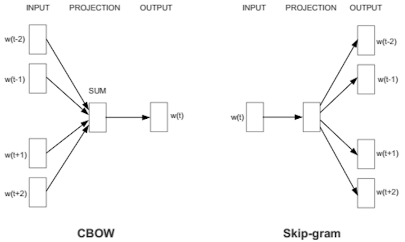

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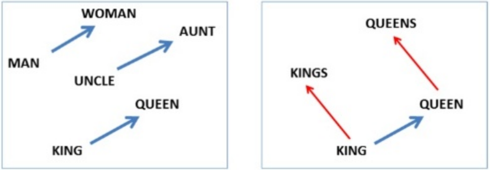

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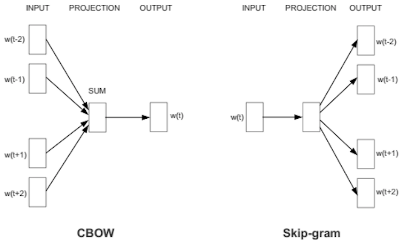

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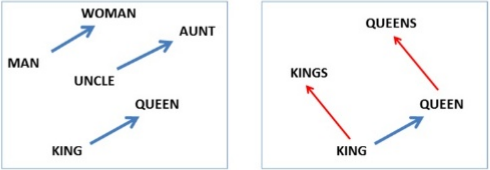

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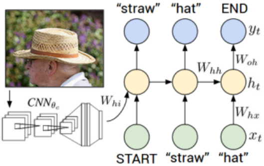

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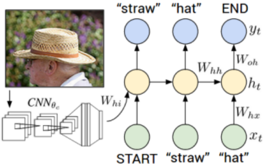

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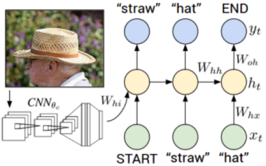

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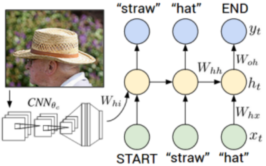

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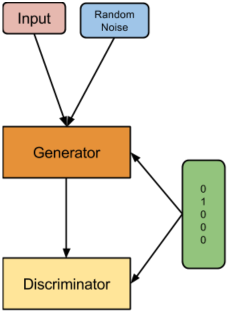

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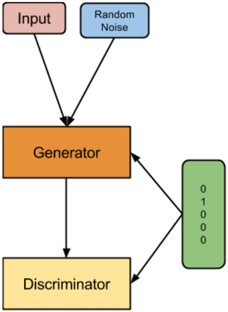
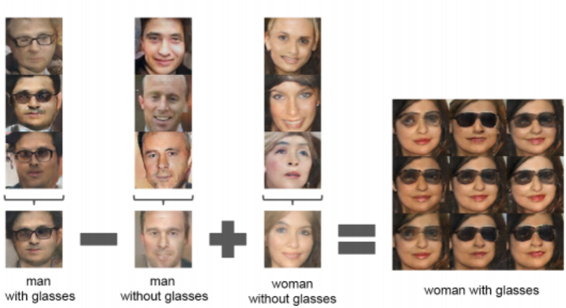
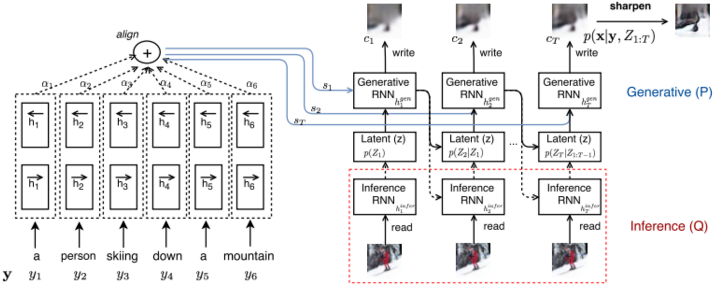
- Most modern idea is like this





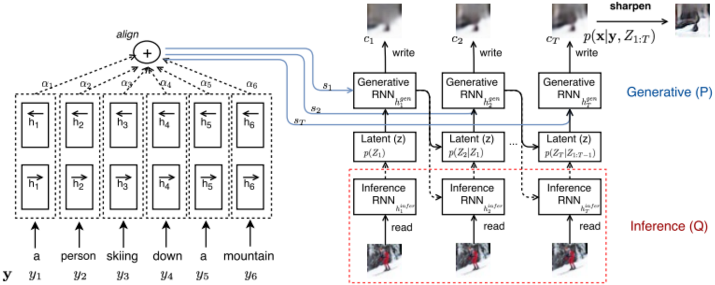
Text2Image

Text2Image



align
+
α_1 α_2 α_3 α_4 α_5 α_6
$\overleftarrow{h}_1$ $\overleftarrow{h}_2$ $\overleftarrow{h}_3$ $\overleftarrow{h}_4$ $\overleftarrow{h}_5$ $\overleftarrow{h}_6$
$\overrightarrow{h}_1$ $\overrightarrow{h}_2$ $\overrightarrow{h}_3$ $\overrightarrow{h}_4$ $\overrightarrow{h}_5$ $\overrightarrow{h}_6$
a person skiing down a mountain
$\mathbf{y}$ y_1 y_2 y_3 y_4 y_5 y_6
s_1
s_2
s_T
c_1 c_2 c_T
write
sharpen
$p(\mathbf{x}|\mathbf{y}, Z_{1:T})$
Generative RNN h_1^{gen}
Generative RNN h_2^{gen}
Generative RNN h_T^{gen}
Generative (P)
Latent (z) $p(Z_1)$
Latent (z) $p(Z_2|Z_1)$
Latent (z) $p(Z_T|Z_{1:T-1})$
...
Inference RNN h_1^{infer}
Inference RNN h_2^{infer}
Inference RNN h_T^{infer}
read
Inference (Q)

Text2Image



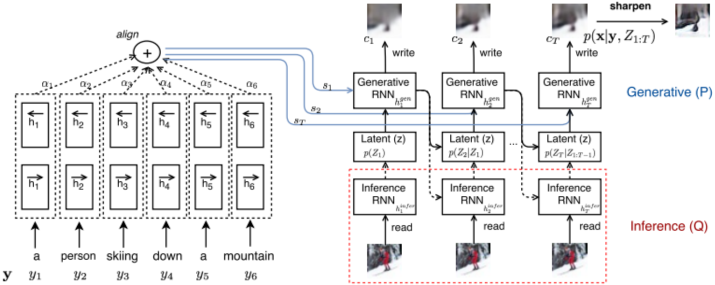

A stop sign is flying in blue skies.


A herd of elephants flying in the blue skies.


A toilet seat sits open in the grass field.


A person skiing on sand clad vast desert.

Text2Image



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https://arxiv.org/pdf/1511.02793v2.pdf

End

Current Status of your Field!

Thanks for your attention!